Aalto University
School of Science

Quality of Analytics as an Approach for Optimizing ML Systems: Initial results and roadmap

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Acknowledgement

- **Include results from joint works with**
  - Matt Baughman, Nifesh Chakubaji, Kyle Chard, Ian Foster (University of Chicago)
  - Krists Kreics (master thesis with Sellforte)
  - Minjung Ryu (master thesis with Solibri)
- **Note: work in progress**

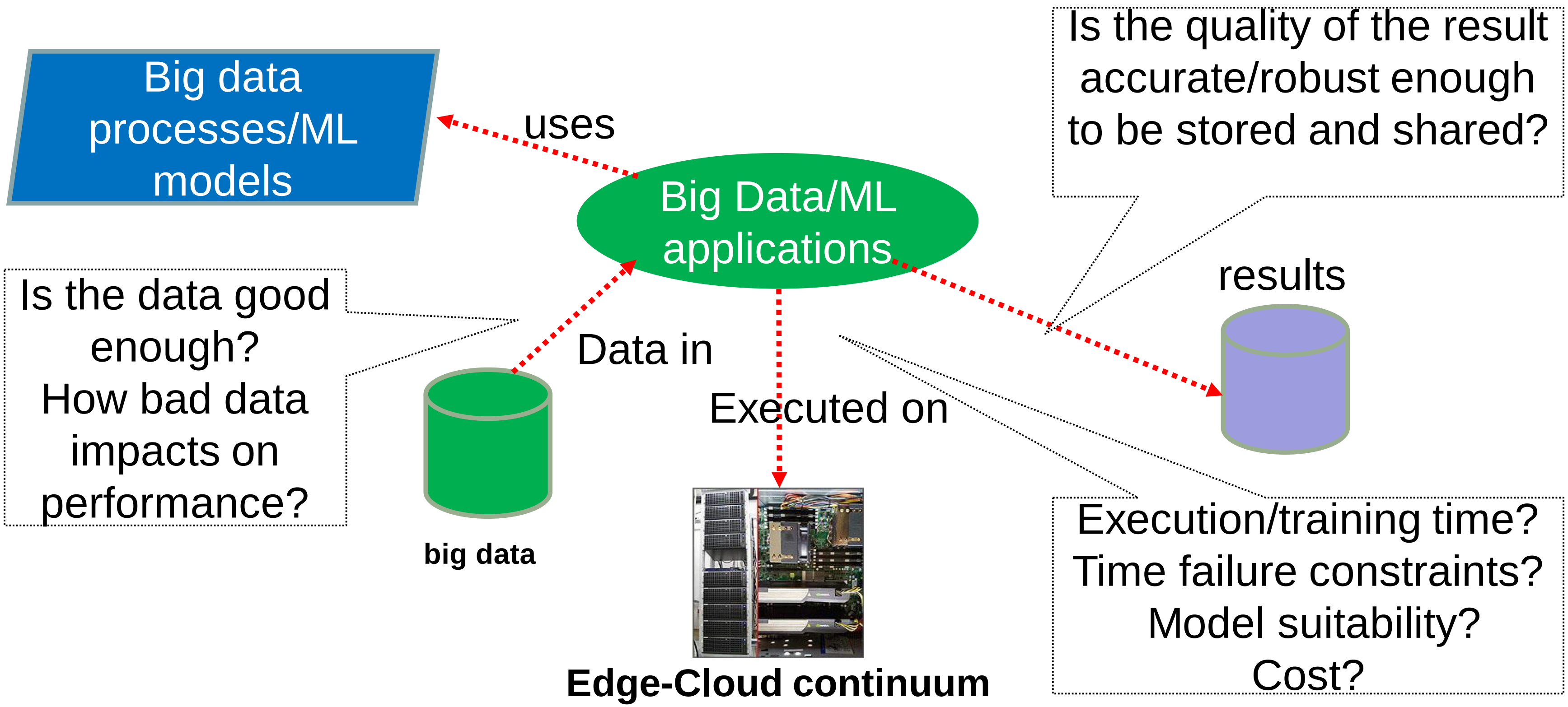
Content

- **Quality of Analytics (QoA) and Principles of Elasticity**
- **QoA-aware optimization for ML systems**
- **Initial results**
- **Next steps and conclusions**

Research focus: optimize the end-to-end ML pipelines

- **Building end-to-end ML (for production) is hard**
  - Several phases from data collection to training to model serving
- **The "system aspect" for ML**
  - Managing dymamic computing and data resources
  - Making ML models serving under "AI as a service" robust, reliable and resilient
- **Optimization from the software systems view**
  - Beyond ML Benchmarks and hyperparameter optimization
  - End-to-end runtime management, ML model serving, and ML experiments

Quality of Analytics (QoA)



QoA

- **Challenges in managing quality across multiple data analytics contexts (DACs).**
  - Interactions with data processing/ML frameworks
  - Interactions with different input and output data sources
  - Interactions with different system services for provisioning, monitoring and control
- **QoA as a composition of multi-dimensional data quality, performance, cost, etc.**
  - QoA as a contract: a "reliable service" should guarantee expected QoA from customers

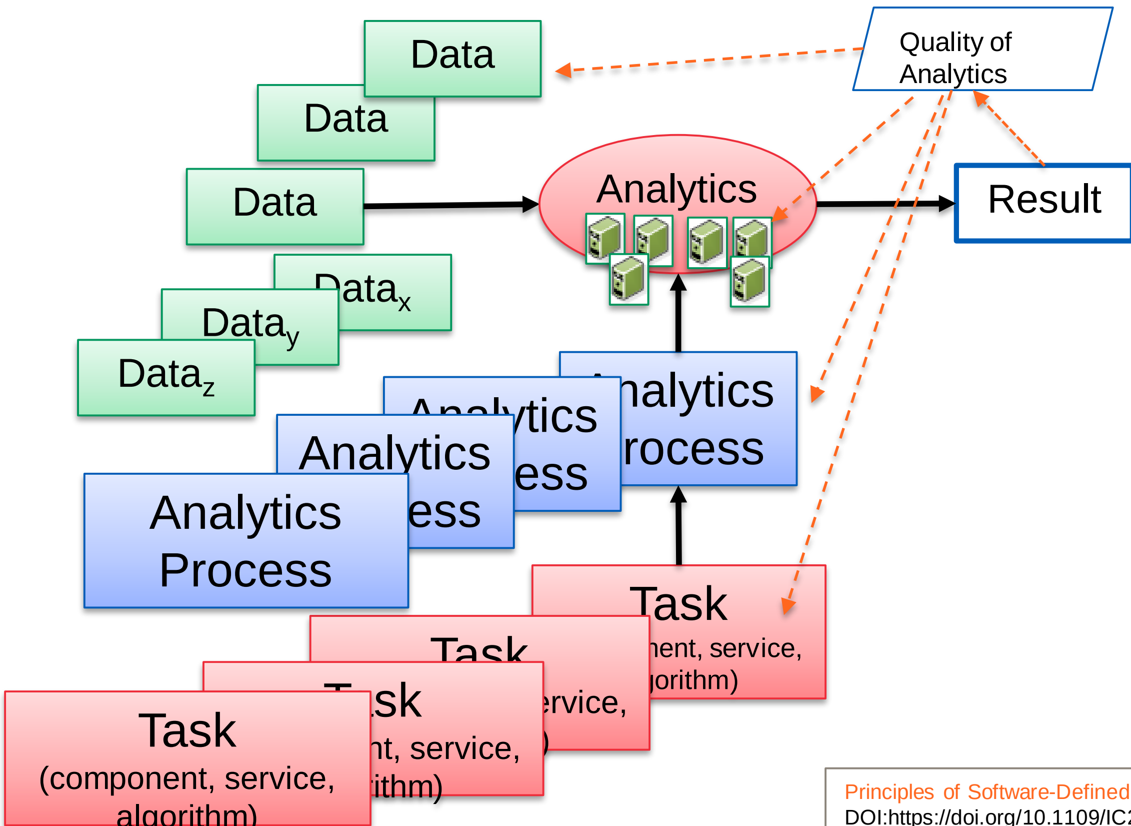
Hong-Linh Truong, Aitor Murguzur, and Erica Yang. 2018. Challenges in Enabling Quality of Analytics in the Cloud. J. Data and Information Quality 9, 2, Article 9 (January 2018), 4 pages. DOI:https://doi.org/10.1145/3138806

Principles of Elasticity

Ability to stretch the "form" under "pressure/force" and return to the normal shape

- **Demand elasticity**
  - Elastic demands from users/customers
- **Output elasticity**
  - Multiple outputs with different price and quality models
- **Input elasticity**
  - Elastic data inputs, e.g., deal with opportunistic data
- **Elastic quality models associated resources and processes**

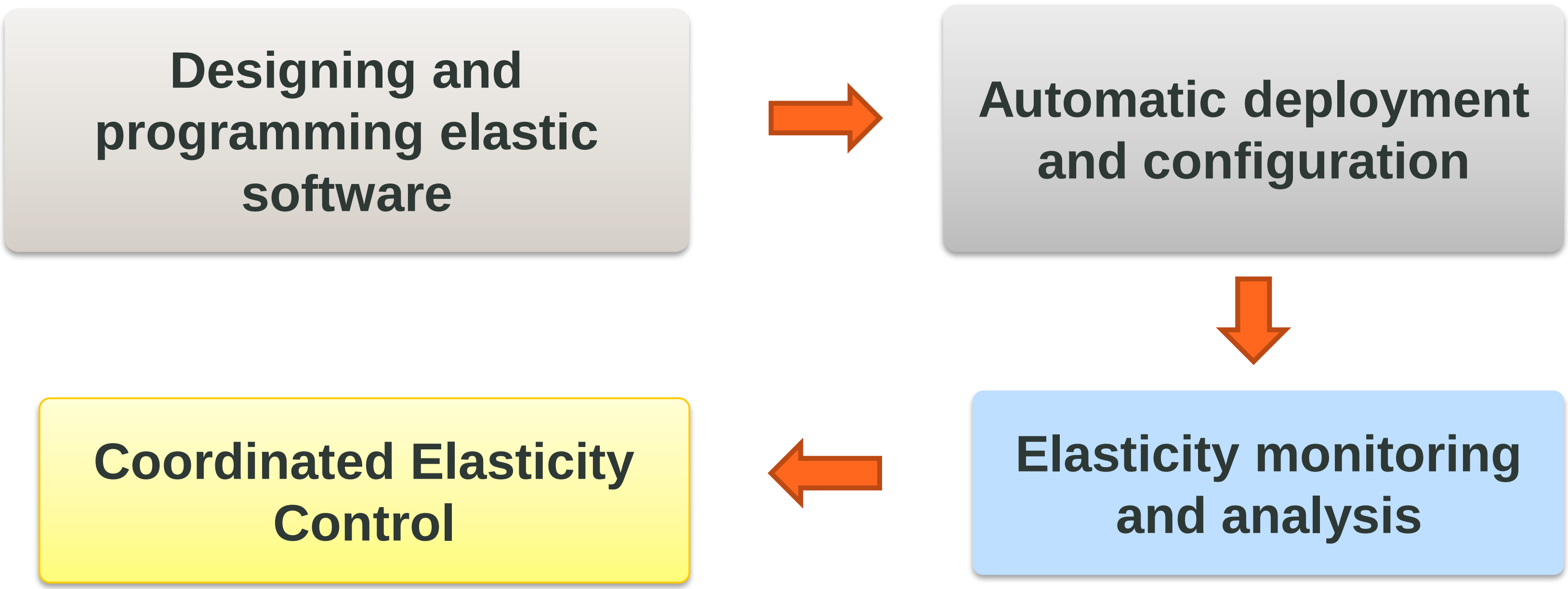
QoA and Multi-dimensional elasticity



- **More data → more compute resources (e.g. more VMs)**
- **More types of data → more, different tasks → more analytics processes**
- **Change quality of analytics**
  - Change quality of data
  - Change response time
  - Change cost
  - Change models and their quality

Principles of Software-Defined Elastic Systems for Big Data Analytics.
DOI:https://doi.org/10.1109/IC2E.2014.67

Elasticity engineering



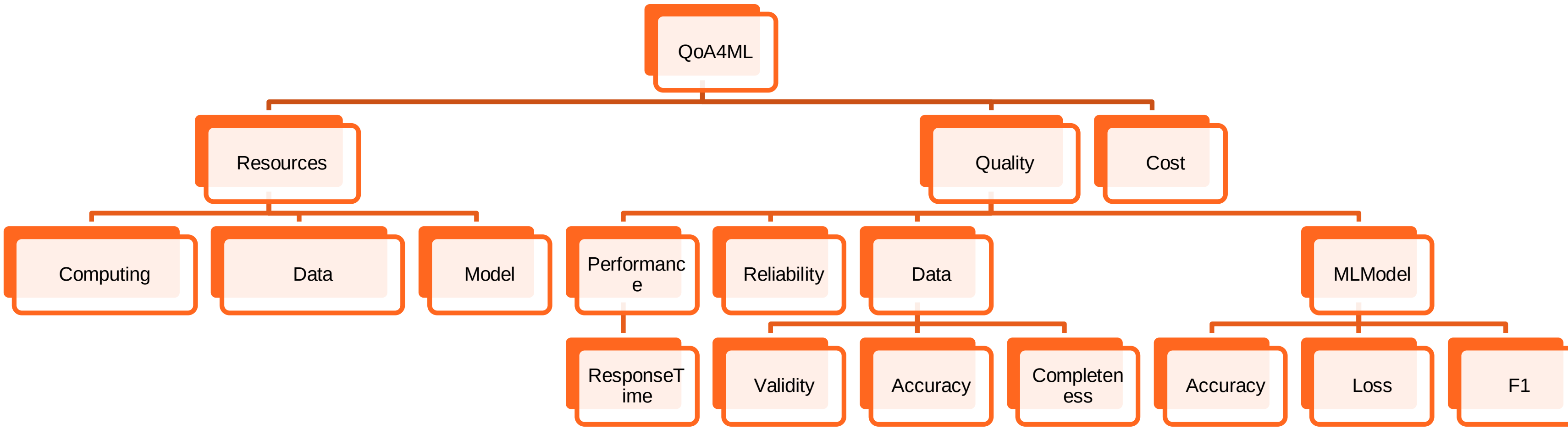
QoA approach for ML systems

QoA as a contract for optimizing ML

- **Quality of analytics: a complex relationships between quality of results, performance and cost**
  - Quality of results are characterized by the users/domain expert, e.g., quality of data of the output, accuracy of the model
  - Inputs have complex characteristics: input data (quality of data, volume) and machines (e.g., computation)
  - Complex types of cost (money) and performance
- **QoA as a contract**
  - The optimization of ML systems is based on the specified QoA
  - Runtime changes and updates by people or intelligent software

Determining most critical elasticity dimensions for ML systems

Example of dimensions

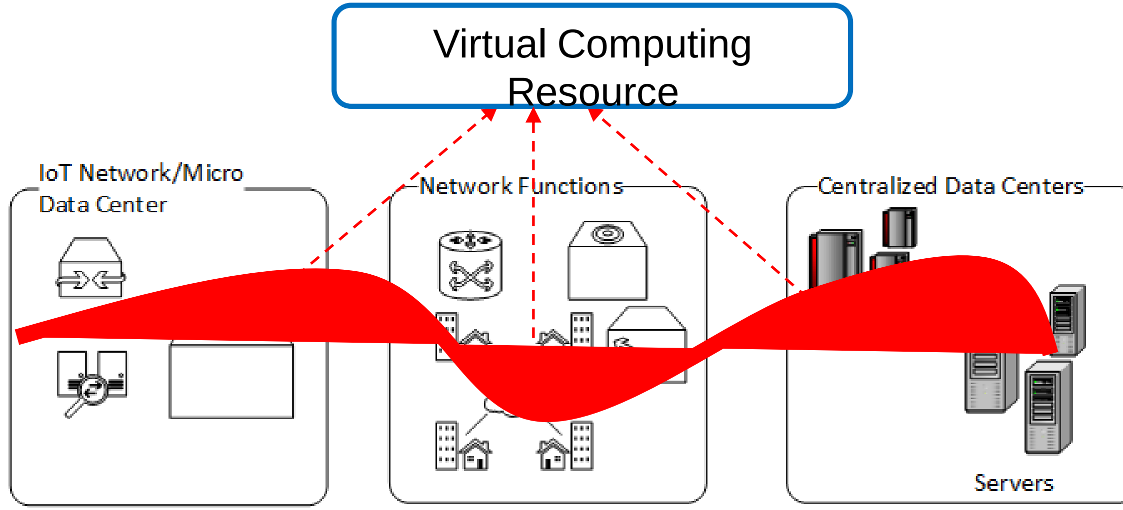


Elasticity engineering for ML

- **Conceptualizing and modeling elastic objects**
  - ML models, computing resources, data and QoA metrics
- **Defining and capturing elasticity primitive operations**
  - Change resources, QoA metrics, model parameters, input data
- **Programming features for elastic objects**
  - With ML flows, coordinating QoA adjustment, dynamic serving models
- **Runtime deploying, control, and monitoring techniques for elastic objects**

Elastic computing resources

Application-specific Resource Ensemble (ASRE)



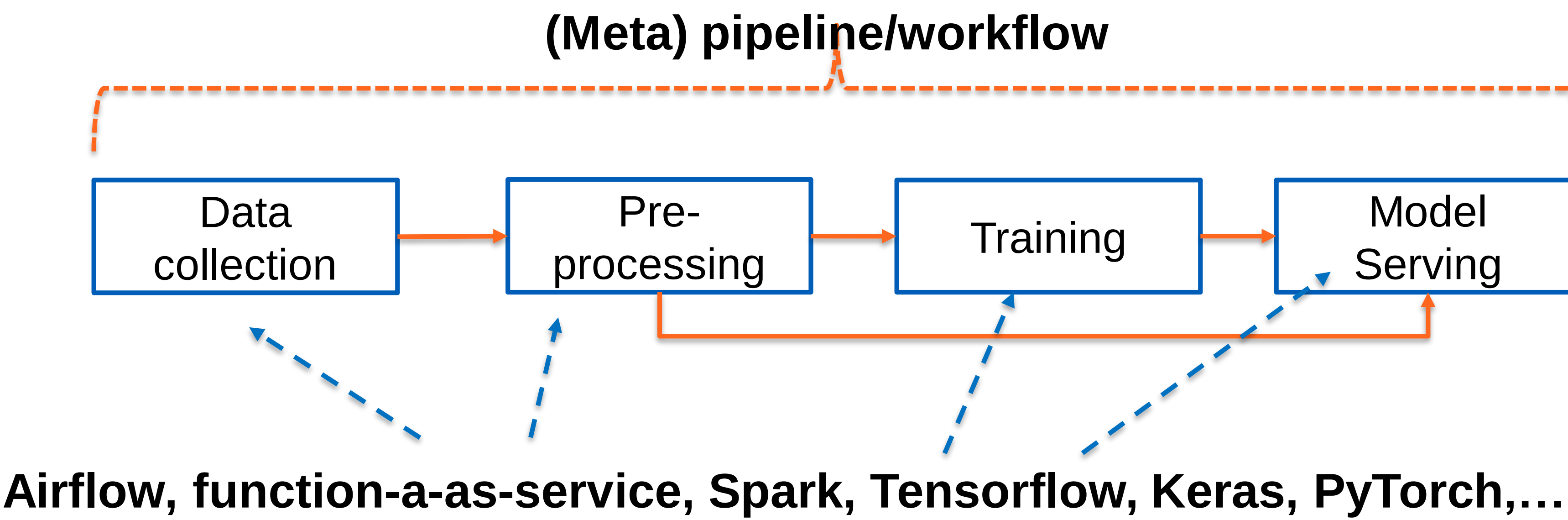
Coral with Edge TPU System-on-Module, Google Edge TPU ML accelerator coprocessor

Jetson NVIDIA (GPU+CPU)

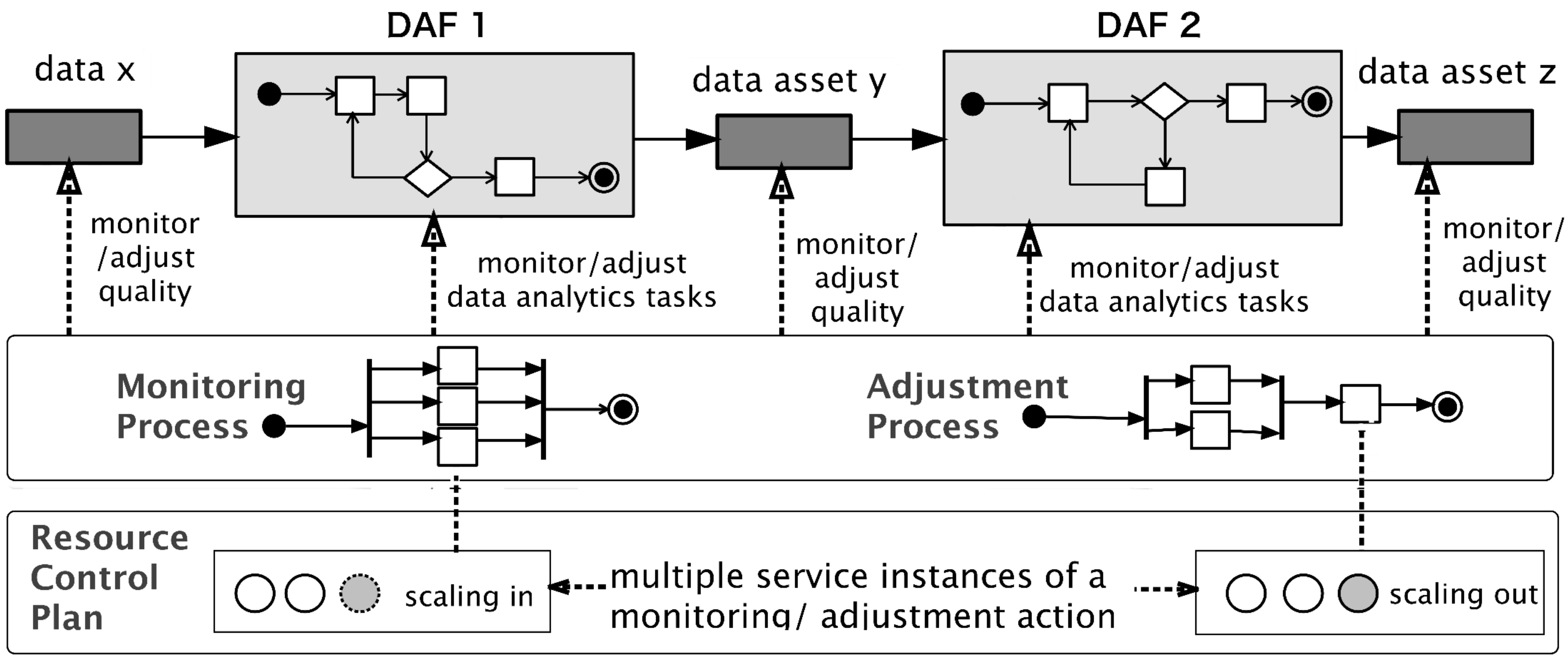
Hong-Linh Truong, ASRE – Application-specific Resource Ensembles across Edges and Clouds, Working paper, 2019

Elastic objects in ML workflows

- **Multiple levels:**
  - Meta-workflow or -pipeline
  - Inside each phase: pipeline/workflow or other types of programs



Elasticity primitive operations for Data Analysis Flows (DAF) model



Source: On Developing and Operating Data Elasticity Management Process. https://doi.org/10.1007/978-3-662-48616-0_7

Some initial results

With results from:

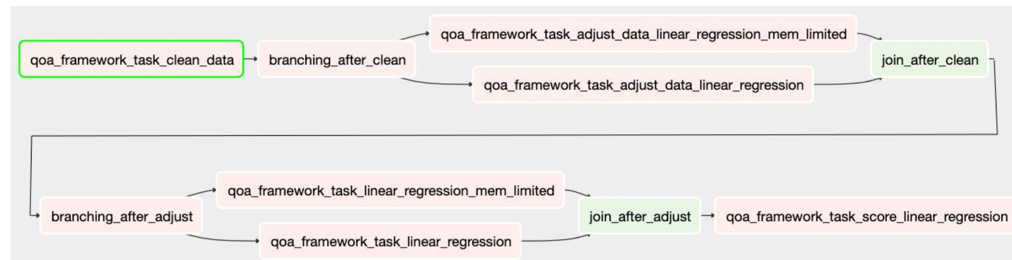
- Kreics Krists, „*Quality of analytics management of data pipelines for retail forecasting*,“, Aalto CS Master thesis, 2019, https://aaltodoc.aalto.fi/handle/123456789/39908
- Minjung Ryu, „*Machine Learning-based Classification System for Building Information Models* “, Aalto CS Master thesis, 2020 (to be finalized)
- Minjung Ryu, Linh Truong, „*Understanding Quality of Analytics Tradeoffs in an End-to-End Machine Learning-based Classification System for Building Information Modeling*”, 2020, Working paper.
- Matt Baughman, Nifesh Chakubaji, Hong-Linh Truong, Krists Kreics, Kyle Chard, Ian Foster, *Measuring, Quantifying, and Predicting the Cost-Accuracy Tradeoff,* IEEE International Workshop on Benchmarking, Performance Tuning and Optimization for Big Data Applications, IEEE BigData 2019, https://research.aalto.fi/files/38801332/paper.pdf

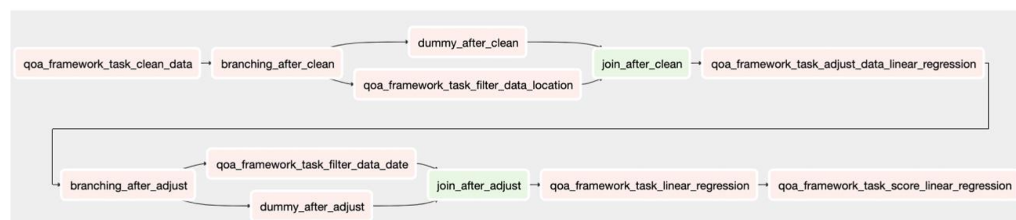
Industrial retail forecast (with Sellforte)

Forecast where to put marketing information, example of data

date	id	name	volume	price	cost	promo	category_net	margin	category1	category2	location	sales
07/01/2018	100	Chicken	38144.0	3.79	2.7	0	451692.0	0.25	Meat	Food	Helsinki	144565.76
14/01/2018	100	Chicken	36420.0	3.79	2.66	0	414342.0	0.25	Meat	Food	Helsinki	138031.8
21/01/2018	100	Chicken	35322.0	3.79	2.66	0	381854.0	0.25	Meat	Food	Helsinki	133870.38

- **Metrics:**
  - Data size, R square value, time, and cost
- **Pipelines**
  - Tune pipelines with QoA primitive actions

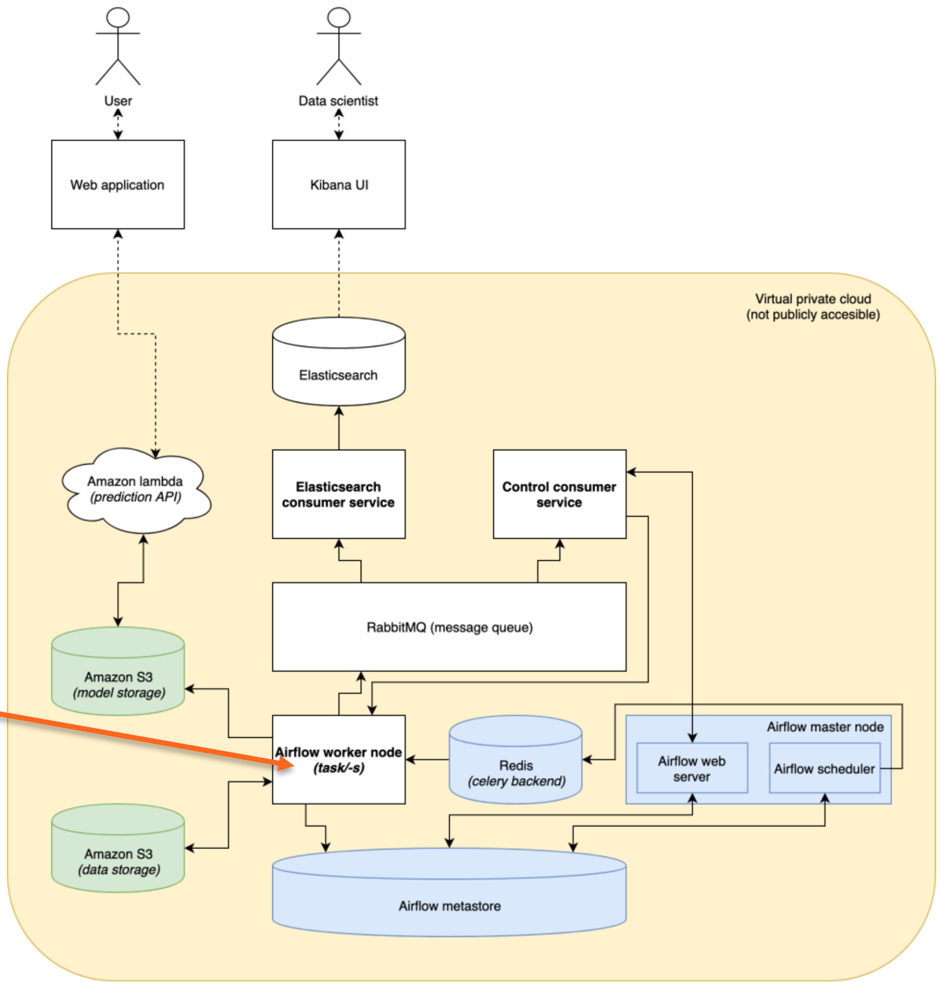




Source: Kreics Krists, „Quality of analytics management of data pipelines for retail forecasting,“, Aalto CS Master thesis, 2019

Industrial retail forecast (with Sellforte)

Monitoring various metrics, including user-defined quality of data



Source: Kreics Krists, „Quality of analytics management of data pipelines for retail forecasting“, Aalto CS Master thesis, 2019

Initial results

Custom cost function

```python
def get_fargate_metrics_object(cpu, ram, elapsed_time, previous_result):
    # Fargate service cost per second
    FARGATE_CPU_COST = 0.04048 / 60 / 60
    FARGATE_RAM_COST = 0.004445 / 60 / 60
    if previous_result and 'cost_usd' in previous_result:
        cpu_cost = previous_result['cost_cpu'] + FARGATE_CPU_COST
        ram_cost = previous_result['cost_ram'] + (ram['used']/1024/1024/1024) * FARGATE_RAM_COST
    else:
        cpu_cost = FARGATE_CPU_COST
        ram_cost = (ram['used']/1024/1024/1024) * FARGATE_RAM_COST

    return { 'cost_cpu': cpu_cost, 'cost_ram': ram_cost, 'cost_usd': ram_cost + cpu_cost }
```

Custom instrumentation for model quality

```python
# model_score returns a dict -> { 'r2_squared': r2_squared_score }
model_score = score_model(store, model, data_path, preset)
pm.log_analytics_metric(model_score)
```

Source: Kreics Krists, „Quality of analytics management of data pipelines for retail forecasting“, Aalto CS Master thesis, 2019

Examples of actions in Elasticity Primitive Operations

```python
def default_get_control_action(body_dict):
    index = body_dict.pop('metric_type', None)
    print(body_dict, flush=True)
    try:
        if index == 'metrics':
            if body_dict['cost_usd'] > 1 or body_dict['time_elapsed'] > 500:
                return 'SOFT_STOP'
            elif body_dict['time_elapsed'] > 1000:
                return 'HARD_STOP'

        elif index == 'data_logs':
            if body_dict['task_name'] == 'clean_data':
                if body_dict['in']['train.csv'] / 2 > body_dict['out']['train.csv']:
                    return 'SOFT_STOP'

        elif index == 'analytics':
            if body_dict['payload']['r2_squared'] < 0.2:
                return 'SOFT_STOP'
        else:
            print('No valid index found!')
            return -1
    except KeyError:
        pass
```

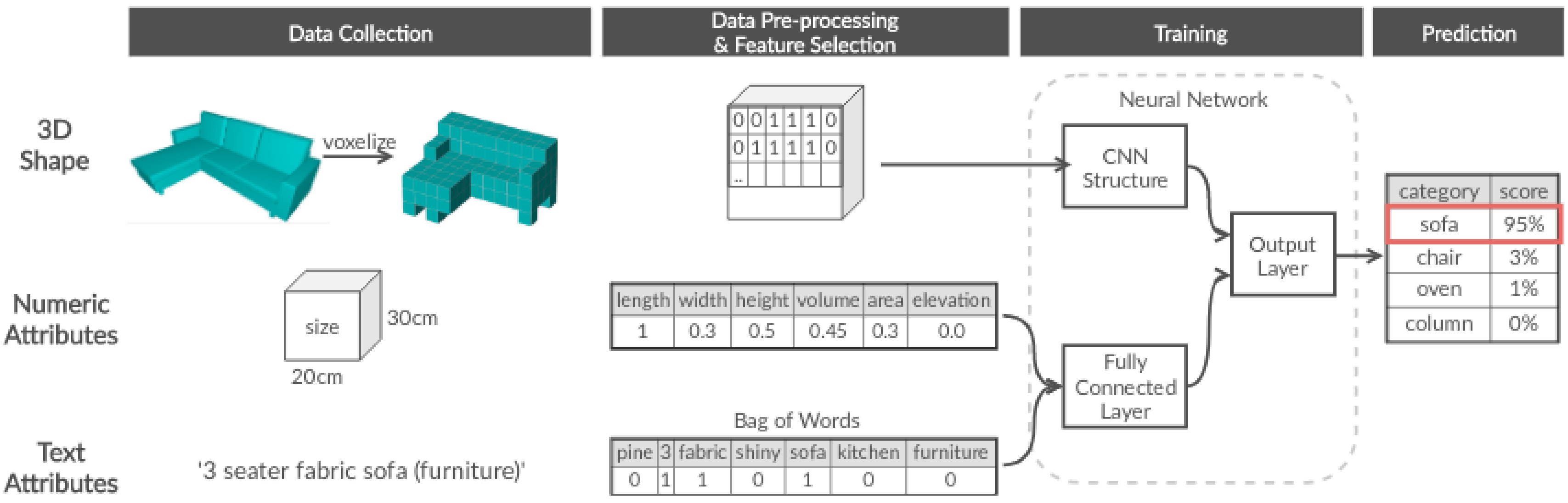
Initial results

- **Running with Airflows in Amazon EC2**
- **Apply different actions to change “store” (domain objects) and computing resources**
- **Real improvement (from the domain expert) with 1 million rows case**

  13.3% lower accuracy and 44% shorter time, R squared value was 9.5% lower → could good enough results for 50% of total store locations

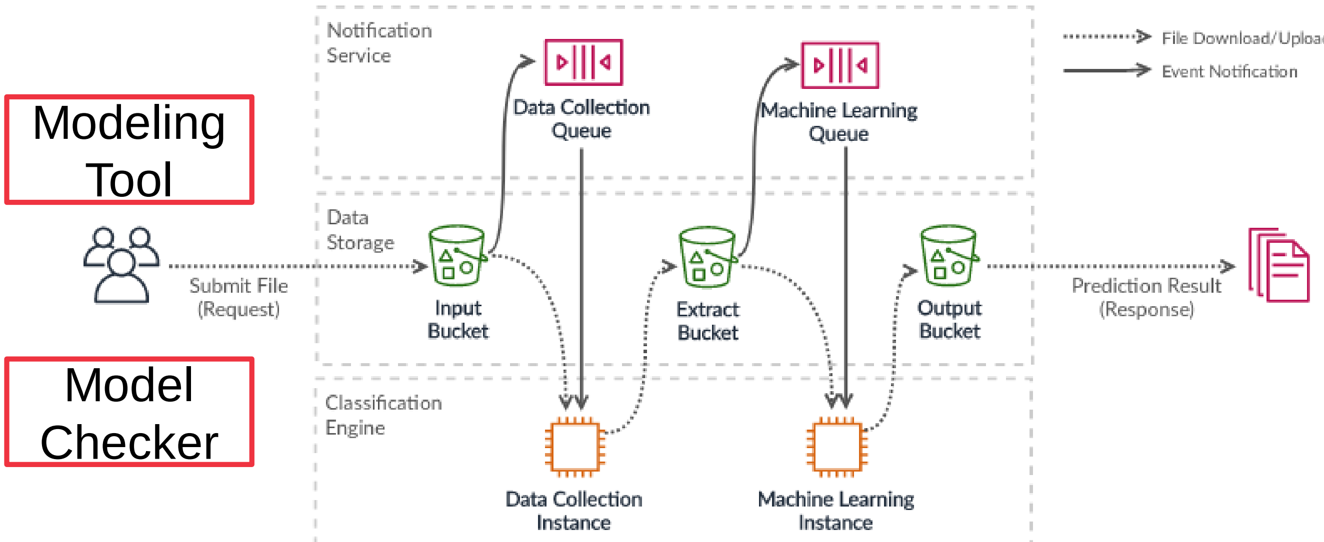
The application-aware data reduction strategy and cost-accuracy tradeoffs may be more intelligently made based on knowledge of the application domain.

ML classification for BIM (with Solibri data)



Source: Minjung Ryu, „Machine Learning-based Classification System for Building Information Models “, Aalto CS Master thesis, 2020

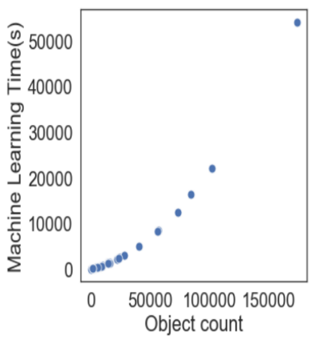
ML classification for BIM (with Solibri data)



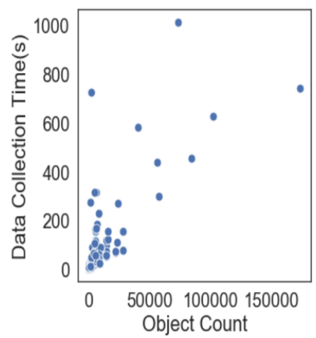
Source: Minjung Ryu, „Machine Learning-based Classification System for Building Information Models “, Aalto CS Master thesis, 2020

Initial results

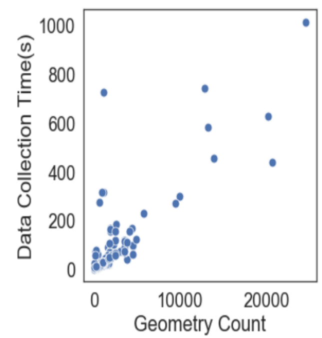
- Data set: 591 classification cases from 146 models
- Machines: AWS/Local with/out GPUs
- Different cases and settings



(a) Object count vs ML time



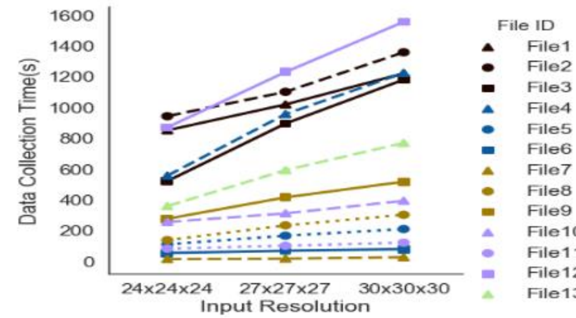
(b) Object count vs DC time



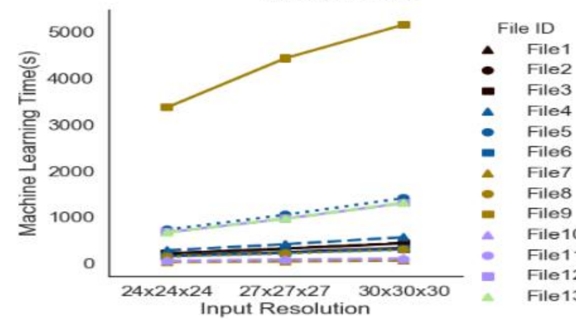
(c) Geometry count vs DC time

Figure 5: Impact of object counts on `DC time` and on `ML time`

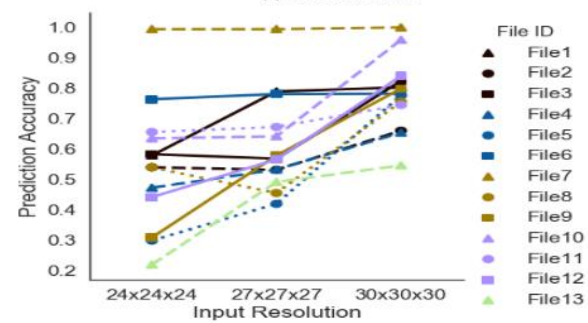
Reveal various relationships between types of data, extracting data resolution, machines and the accuracy of classifications



(a) Dim vs DC time



(b) Dim vs ML time



(c) Dim vs Accuracy

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Roadmap: Robustness, Reliability, Resilience and Elasticity (R3E) with QoA

QoA as an approach for ML optimization

- **A conceptual framework for defining Quality of Analytics (QoA)**
  - Metrics for services, data and ML models
  - Human-in-the-loop and domain expert integration
- **QoA as "contract"**
  - Leverage service contract and data contract models for QoA4ML
- **Monitoring and mechanisms for measuring QoA**
  - Measuring accuracy for data and models is challenging
  - Integration with data validation and model validation tools

QoA as an approach for ML optimization

- **Application-specific Resource Ensembles**
  - Resource ensembles are provisioned based on QoA
  - Containers and Kubernetes are key technologies for elastic edge-cloud platforms
- **QoA-aware and ML flow coordination**
  - Elasticity Primitive Operations
    - *Also leveraging quality data controllers and data governance processes in big data for ML?*
  - Elastic ML model serving platform-as-a-service
    - *Suitable for ensemble and federated ML?*

QoA as an approach for ML optimization

- **Models for predicting QoA**
  - Need to develop models capable of predicting QoA (of data and ML models)
- **Methods for adaptation and optimization**
  - Enable users to explore QoA tradeoffs such that they can inform application development and use
  - Integrate with different approaches to QoA-aware distributed computing

Conclusions

- **QoA can be used as a contract for Robustness, Reliability, Resilience and Elasticity (R3E) of ML**
  - Selected scenarios: training optimization, runtime ML model serving, out-of-distribution detection and optimization
- **Elasticity Engineering**
  - Can be a powerful techniques for achieving QoA in ML systems
- **Need real, complex ML systems for testing our ideas!**
- **Collaboration with FCAI is really important!**

Thanks!

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